Table 11 Summary of AQM schemes with online training in the intermediate nodes of a wired network

Ref.	ML Technique	Multiple Bottleneck[a]	Synthetic data from ns-2 simulation	Features	Output (action-set for RL)	Evaluation Settings	Evaluation Results
PAQM [160]	Supervised: · OLS	✓	Topology: · 6-linear · Arbitrary dumbbell Time = 50*s*	· Traffic volume (bytes)	TSF: · Traffic volume	· NMLS algorithm based on LMMSE	Accuracy: · 90 − 92.3%
APACE [212]	Supervised: · OLS	✓	Topology: · Dumbbell (1-sink) · 6-linear Time = 40*s*	· Queue length	TSF: · Queue length	· NMLS algorithm based on LMMSE	Accuracy: · 92%
α_SNFAQM [498]	Supervised: · MLP-NN	–	Topology: · Dumbbell (1-sink) Time = 300*s*	· Traffic volume · Predicted traffic volume	TSF: · Traffic volume	· 2 input neurons · 2 hidden layers with 3 neurons · 1 output neuron	Accuracy: · 90 − 93%
NN-RED [179]	Supervised: · SLP-NN	–	Topology: · Dumbbell Time = 900*s*	· Queue length	TSF: · Queue length	· 1+*N* input neurons (*N* past values) · 0 hidden layers · 1 output neuron · Delta-rule learning	*N/A*
DEEP BLUE [298]	Reinforcement: · Q-learning - ϵ-greedy	–	Topology: · Dumbbell Time = 50*s* *OPNET simulator instead of ns-2*	States: · Queue length · Packet drop prob. Reward: · Throughput · Queuing delay	Decision making: · Increment of the packet drop probability *(finite: 6 actions)*	· *N/A* states · 6 actions · ϵ-greedy ASS[b]	Optimal packet drop probability: · Outperforms BLUE [144]
Neuron PID [428]	Reinforcement: · PIDNN	✓	Topology: · Dumbbell Time = 100*s*	· Queue length error	Decision making: · Increment of the packet drop probability *(continuous)*	· 3 input neurons · 0 hidden layers · 1 output neuron · Hebbian learning · 1 PID component	QL_{Acc} error[c]: · 7.15 QL_{Jit}: · 20.18
AN-AQM [427]	Reinforcement: · PIDNN	✓	Topology: · Dumbbell · 6-linear Time = 100*s*	· Queue length error · Sending rate error	Decision making: · Increment of the packet drop probability *(continuous)*	· 6 input neurons · 0 hidden layers · 1 output neuron · Hebbian learning · 2 PID components	QL_{Acc} error[c]: · 6.44 QL_{Jit}: · 22.61
FAPIDNN [485]	Reinforcement: · PIDNN	✓	Topology: · Dumbbell Time = 60*s*	· Queue length error	Decision making: · Increment of the packet drop probability *(continuous)*	· 3 input neurons · 0 hidden layers · 1 output neuron · 1 PID component · 1 fuzzy component	QL_{Acc} error[c]: · 3.73 QL_{Jit}: · 31.8
NRL [499]	Reinforcement: · SLP-NN	✓	Topology: · Dumbbell Time = 100*s*	· Queue length error · Sending rate error	Decision making: · Increment of the packet drop probability *(continuous)*	· 2 input neurons · 0 hidden layers · 1 output neuron · RL learning	QL_{Acc} error[c]: · 38.73 QL_{Jit}: · 128.84

[a] Specifies if the approach was evaluated for multiple bottleneck links (✓) or simply for a single bottleneck link (–)
[b] Action Selection Strategy (ASS)
[c] Value computed using RMSE on the results presented in [269] for different network conditions

On the other hand, DEEP BLUE [298] focus on addressing the limitations of BLUE [144], an AQM scheme proposed for improving RED. BLUE suffers from inaccurate parameter setting and is highly dependent on its parameters. DEEP BLUE addresses these problems by introducing a fuzzy Q-learning (FQL) approach that learns to select